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Impacts of heat, cold, and temperature variability on mortality in Australia, 2000–2009

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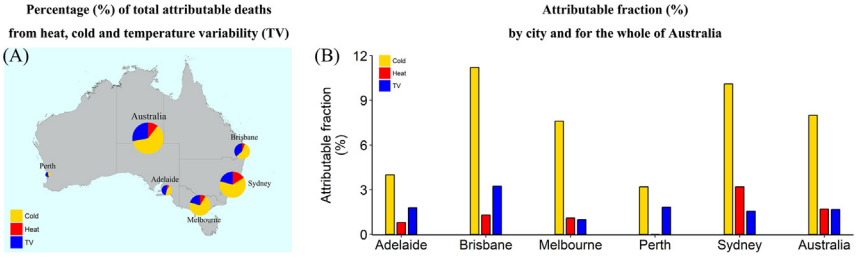
HIGHLIGHTS

- Heat, cold, and temperature variability (TV) could increase mortality in Australia.
- Mortality risk from any temperature exposure did not increase or decrease over time.
- Cold posed the greatest mortality risk and cased the largest mortality burden.
- TV posed the lowest mortality risk but cased more mortality burden than heat.
- Heat, cold, and TV together accounted for about 6.0% of all deaths.

GRAPHICAL ABSTRACT



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ABSTRACT

Objectives: Evidence is limited on the relative contribution of different temperature exposures (i.e., heat, cold and significant temperature variability) to mortality. This study aims to examine mortality risk and associated mortality burden from heat, cold, and temperature variability in Australia.

Methods: We collected daily time-series data on all-cause deaths and weather variables for the five most populous Australian cities (Sydney, Melbourne, Brisbane, Adelaide, and Perth), from 2000 to 2009. Temperature variability was calculated from the standard deviation of hourly temperatures between two adjacent days. Three-stage analysis was used. We firstly used quasi-Poisson regression models to model the associations of mortality with heat (mean temperature) during the warm season, with cold (mean temperature) during the cold season, and with temperature variability all year round, while controlling for long-term trend and seasonality, day of week, and population change over time. We then estimated the effects of different non-optimum temperatures using the simplified log-linear regression model. Finally, we computed and compared the fraction (%) of deaths attributable to different non-optimum temperatures.

Results: The greatest percentage increase in mortality was for cold (2.0%, 95% confidence interval (CI): 1.4%, 2.6%), followed by heat (1.2%, 95% CI: 0.7%, 1.7%), and temperature variability (0.5%, 95% CI: 0.3%, 0.7%). There was no clear temporal pattern in mortality risk associated with any temperature exposure in Australia. Heat, cold and temperature variability together resulted in 42,414 deaths during the study period, accounting for about 6.0% of all deaths. Most of attributable deaths were due to cold (61.4%), and noticeably, contribution from temperature variability (28.0%) was greater than that from heat (10.6%).

Conclusions: Exposure to either cold or heat or a large variation in temperature was associated with increased mortality risk in Australia, but population adaptation appeared to have not occurred in most cities studied.

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Most of the temperature-induced deaths were attributable to cold, and contributions from temperature variability were greater than that from heat. Our findings highlight that, in addition to heat and cold, temperature variability needs to be considered in assessing and projecting the health impacts of climate change.

1. Introduction

Ambient temperatures have impacts on human health worldwide (Basu and Samet, 2002; Gasparrini et al., 2015a). Existing epidemiological evidence suggests increased mortality risk in relation to heat or cold or both in many regions of the world (Gasparrini et al., 2015a; Lee et al., 2017). Recently, temperature variability within and between days was also widely recognised as an important and independent risk factor (Guo et al., 2016; Cheng et al., 2017). These non-optimum temperatures already cause substantial disease burden in many countries and is of increasing concern in the context of climate change (Gasparrini et al., 2015a; Cheng et al., 2017; Zhang et al., 2018).

Compared with heat and cold exposures that are largely confined to the warm and cool seasons respectively, temperature variability can happen all year round and may result in similar or greater health impacts (Cheng et al., 2017; Zhang et al., 2018). Also, reductions in heat or cold effects are possible after accounting for the influence of temperature variability, and vice versa (Guo et al., 2016). More accurate estimates of the relative contributions of different temperature exposures can be achieved through incorporating the temperature variability into analysis. Although there are numerous studies of temperature and mortality conducted in countries such as the UK, USA, China and Australia, temperature variability has seldom been considered when investigating the mortality effects of heat or cold or both (Gasparrini et al., 2015a; Vicedo-Cabrera et al., 2016), and very few studies have compared the mortality effects of temperature variability with that of heat or cold (Lee et al., 2017).

Minimum mortality temperature (MMT) at which the mortality risk is lowest has been most often used in previous studies to obtain quantitative effect estimates for non-optimum temperatures (Gasparrini et al., 2015a; Lee et al., 2017). Those studies focused on detecting the uniform threshold (MMT) for heat and cold but did not consider the possibility that individuals have certain thermoregulation capacity, and populations within a region may not be affected within a certain temperature range (Guo et al., 2011; Li et al., 2013). We argue that modelling the temperature-mortality association for heat and cold separately provides a useful supplementary tool to augment the traditional temperature threshold identification and temperature-related health effects assessment, because it takes account of the seasonal limitations for the occurrence of different exposures and helps reduce concerns regarding the unknown or unmeasured season-related confounders, such as infectious disease epidemics (Petitti et al., 2016).

The objective of this study was to evaluate the relative contribution of three common non-optimum temperature exposures (i.e., heat, cold and temperature variability) to mortality and investigate whether population adaptation has been well established with an analysis of the largest ever multi-city data in Australia.

2. Materials and methods

2.1. Data collection

Time-series data on death and weather variables were collected for the period 2000–2009 in the five largest cities of Australia (Sydney, Melbourne, Brisbane, Adelaide, and Perth). In this period, these cities comprised over 60% of the Australian population residing in different climate zones and having distinct demographic and socioeconomic characteristics (Cheng et al., 2017).

Daily counts of death for all causes were provided by Australian Bureau of Statistics. This data was assembled during the same period (2000–2009) for all cities included. We obtained data on daily maximum and minimum temperatures, and hourly temperatures from Australia Bureau of Meteorology. Daily mean temperature was calculated by the average of daily maximum and minimum temperatures and then selected as the exposure index (Gasparrini et al., 2015a; Cheng et al., 2018a). Temperature variability was calculated from the standard deviation of hourly temperatures between two adjacent days (Cheng et al., 2017). Other data on relative humidity and air pollution (ozone, nitrogen dioxide, particulate matter with aerodynamic diameter <10 μm) were available only in the subset of cities and served as sensitivity analysis. We have also reported this dataset elsewhere (Cheng et al., 2017; Cheng et al., 2018a).

This study was approved by the Human Research Ethics Committee at the Queensland University of Technology (approval number: 1700000848). Because the data were de-identified and aggregated, written consent was not needed.

2.2. Statistical analyses

Our statistical analyses consisted of three stages. In the first stage, we applied a time-series regression to model the potential non-linear temperature-mortality association and identify the MMT for different temperature exposures (Gasparrini et al., 2015a). In the second stage, we estimated the effects of different non-optimum temperatures, reported as relative risk (RR) and 95% confidence interval (CI) using the simplified log-linear regression model (Curriero et al., 2002; Gasparrini et al., 2012; Cheng et al., 2016; Vardoulakis et al., 2014). Temporal variation in the temperature effects over study period was also investigated. In the third stage, we computed and compared the fraction (%) of deaths attributable to different non-optimum temperatures following previous experience in similar studies (Gasparrini et al., 2012; Vardoulakis et al., 2014; Cheng et al., 2017). Each stage was described in more detail below.

2.2.1. Stage 1: city-specific temperature-mortality associations for different temperature exposures

For each city, we used the generalized additive model (GAM) with a quasi-Poisson link to fit the associations of mortality with heat during warm season (November to March of next year) (Tong et al., 2015; Cheng et al., 2018b), with cold during cool season (May to September) (Cheng et al., 2018b), and temperature variability all year round, respectively. The applied city-specific time-series model for heat and cold took the form:

$$\mathrm{Log}\,(M) = \alpha + s\,(Tem, k = 4) + TV + ns\,(time, df) + \beta * Dow + offset\,(POP);$$

where M is the daily time-series counts of death; α is the intercept; $s\,()$ is the fitted thin-plate regression spline with k-1 degrees of freedom for the temperature during warm or cool season (Petitti et al., 2016), with a lag up to 1 day for heat (moving average of lags 0–1) and up to 21 days for cold (moving average of lags 0–21) (Gasparrini et al., 2015a; Gasparrini et al., 2012); Temperature variability (*TV*) were included as a potential confounder; Other confounders to be controlled for here included long-term trend and seasonality with a natural cubic spline (*ns*) of three degrees of freedom for *time* and day of the week (*Dow*) as the

categorical variable; *POP* refers to each year's population in log scale, which was used as an offset to control for potential confounding effect of demographic shifts (change in the size of population) over time (Qiao et al., 2015).

City-specific time-series model for temperature variability has been done in our previous analyses (Cheng et al., 2017). Briefly, we observed an approximately linear relationship between mortality and temperature variability in all Australian cities studied, and 1 °C rise in temperature variability corresponded to mortality increase of 0.28% to 1.00%, with an average increase of 0.51%. It was also estimated that temperature variability accounted for 0.99% to 3.24% of deaths across cities, with a nation-wide attributable fraction of 1.67%. The estimates (i.e., relative risk (RR) and attributable burden) of this study were used for the present analysis.

MMT for heat and cold was separately identified from the city-specific smoothed curves of temperature-mortality association. In the present study, MMT for heat was defined as the temperature above which a consistent increase in mortality risk was observed (i.e., the slope of the exposure-response curve was always positive above MMT), and MMT for cold was defined as the temperature below which there was always a consistent increase in mortality risk (Petitti et al., 2016; Cheng et al., 2018b). This method could help differentiate the relative comfort or healthy temperature range from the study period of interest.

2.2.2. Stage 2: estimation of temperature effects and temporal variation

The purpose of this stage is to know exposure to which non-optimum temperature exerts the greatest risk (RR) in general, and how this effect estimates changed over time as a reflection of population's vulnerability. The identified MMT in Stage 1 was used as the reference to calculate the mortality risk (Petitti et al., 2016; Cheng et al., 2018b). To ease the interpretation and facilitate comparisons of effect estimates, piece-wise linear model (in log scale) was used for each city under the framework of distributed lag non-linear model. This model was in line with many earlier studies (Cheng et al., 2016; Cheng et al., 2018b; Gasparrini et al., 2012; Vardoulakis et al., 2014; Curriero et al., 2002), and further justified by our modelled temperature-mortality dose-response curves suggesting that the mortality risk approximately linearly elevated with temperature increase above heat-MMT and with temperature decrease below cold-MMT (Fig. 1). The estimated slope (β) of exposure-response curve was transformed using the formula *exp*( ), which can be interpreted as the RR associated with 1 °C rise for heat or 1 °C drop for cold (Armstrong et al., 2017).

To unravel the temporal evolution in the effects of different temperature exposures, we performed a time-stratified analysis by running the city-specific piece-wise linear model for each 3-y period (changed the study period by one year at a time) (Renzi et al., 2017). For example, the first data point created to do the analysis was for the period 2000–2002, the second for 2001–2003, and so forth until the last data point, which corresponded to the period 2007–2009. The derived effect estimates (RR) for each temperature exposure were fitted with smooth function of natural cubic spline with three degrees of freedom allowing for more complex fluctuations, in addition to roughly increasing or decreasing trend. Other alternative methods such as adding an interaction term between daily temperature and the year of death to the model or using time-stratified analysis by each 4-y period were used as the sensitivity analysis (Renzi et al., 2017), which generated analogous results (data not shown).

A meta-analysis was used to pool the city-specific effect estimates obtained from the above-mentioned analyses. This meta-analysis was fitted using a random-effects model by maximum likelihood to generate the national pooled estimates. For the comparison of effect estimates among different temperature exposures, we carried out a meta-regression analysis with temperature exposure as the categorical variable. Significance level was set at $P < 0.05$.

2.2.3. Stage 3: attributable burden calculation

The estimated slope (β) of temperature-mortality associations in Stage 2 were used to calculate the attributable burden, in terms of both attributable fraction and attributable number, using a previously described method (Cheng et al., 2017; Vardoulakis et al., 2014). For each day of the time-series (i) with the occurrence of temperature exposure (j), the attributable fraction (*AF*) and attributable number (*AN*) were computed in each city (k) using the following formula:

$$AF_{ijk} = \frac{RR_{ijk} - 1}{RR_{ijk}};$$

$$AN_{ijk} = AF_{ijk} * D_{ijk};$$

where $RR_{ijk} = exp\ (\beta_{jk} | Tem_{ijk} - MMT_{jk}|\ )$; and $D_{ijk}$was the number of deaths on day (i) in city (k).

Daily attributable deaths were then summed over days to get the total attributable deaths for different temperature exposures in each city, and its ratio with the total deaths during the study period will be the total attributable fraction. The national attributable fraction was also calculated by dividing the estimated total attributable deaths by the total observed deaths across all cities.

All the data analyses were conducted in R software (version 3.4.0, R Foundation for Statistical Computing, Vienna, Austria) and analytical code to reproduce the analysis is available on request from the first or corresponding author.

3. Results

Table 1 shows the summary of deaths and mean temperature for the five largest cities in Australia. This study included 708,751 deaths in the period 2000–2009, and warm season and cool season together comprised about 84% of total deaths. The average city-specific daily mean temperature was in the range of 14.4 °C–20.7 °C, with the highest and lowest values recorded in Brisbane and Melbourne, respectively, regardless of the season.

Fig. 1 displays the associations of mortality with heat, and with cold. Temperature variability-mortality association was reported in our previous study (Cheng et al., 2017). Except for the city of Perth, both heat and cold were associated with increased mortality risk in the remaining four cities. Increased mortality risk with rises in temperature variability was seen in all cities (Cheng et al., 2017). The identified MMT varied greatly across cities, ranging from 18.3 °C in Sydney to 26.1 °C in Perth for heat (Fig. 1A), and from 11.0 °C in Melbourne to 21.4 °C in Brisbane for cold (Fig. 1B).

The risk estimates for different temperature exposures are shown in Table 2. The RRs associated with heat, cold and temperature variability across cities varied between 1.001 and 1.029, 1.008 and 1.026, and 1.003 and 1.010, respectively. On average, cold was associated with the greatest risk (RR = 1.020, 95% confidence interval (CI): 1.014, 1.026), followed by heat (RR = 1.012, 95% CI: 1.007, 1.017) and temperature variability (RR = 1.005, 95% CI: 1.003, 1.007).

Fig. 2 shows the temporal changes in the RR estimates of heat, cold and temperature variability for each city, as well as for Australia as a whole. Clear and consistent trend was observed only for some exposures in few cities. For instance, decreasing trend appeared to happen for heat in Brisbane and for cold in Perth. In contrast, increasing trend was noted for cold in Brisbane and for temperature variability in Melbourne. The remaining combinations exhibited periodic or more complex changes such as early downward trend and later upward trend for cold in Sydney and Melbourne, or early downward trend and mid-term upward trend and later downward trend for temperature variability in Adelaide, described as U-, V- or W-shape pattern. In total, there is no clear evidence of consistent increases or decreases in the mortality risk associated with all exposures in Australia.

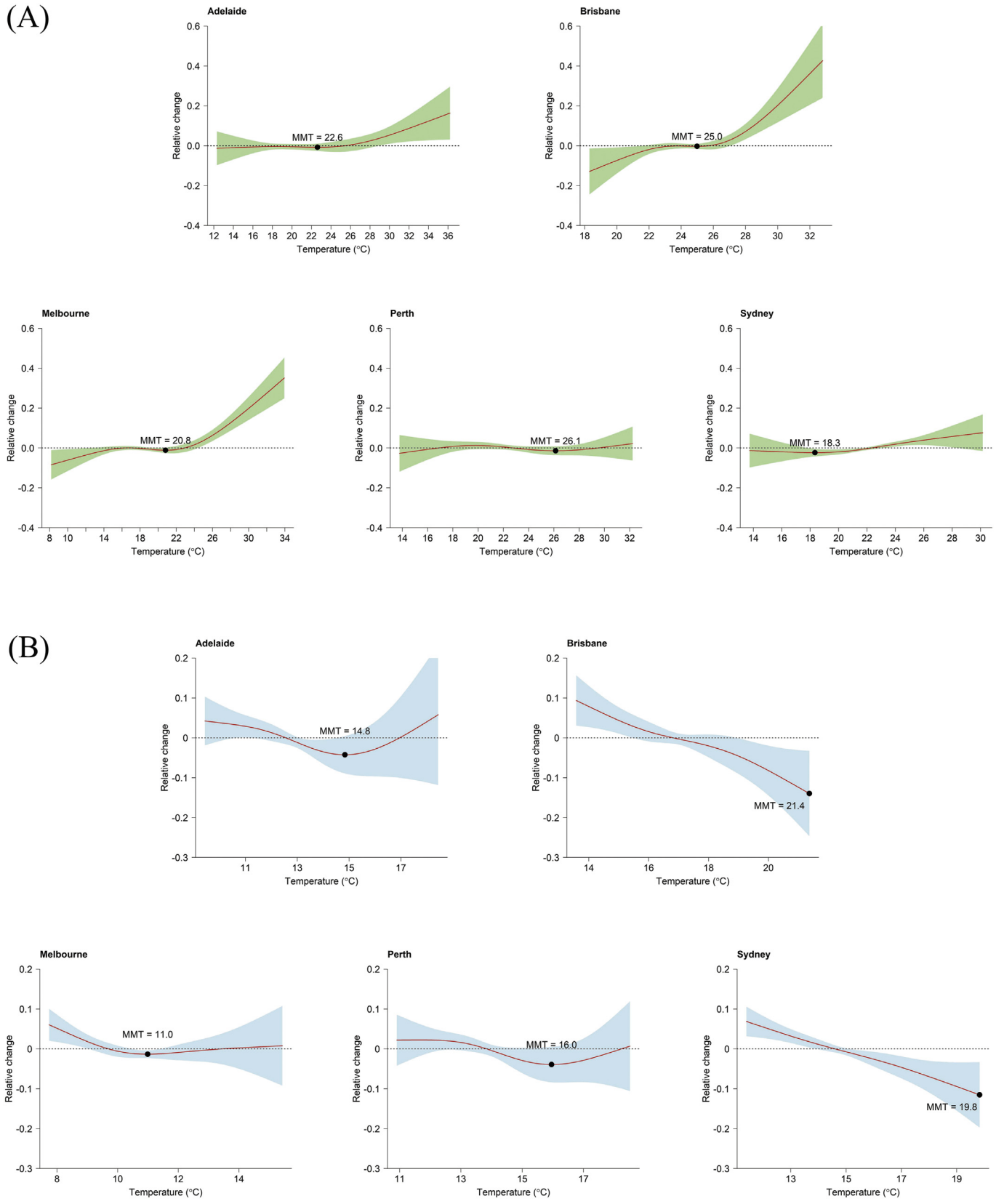

Fig. 1. The exposure-response association of mortality with heat (A) and cold (B) in five cities of Australia, 2000–2009. MMT is the minimum mortality risk.

It was estimated that heat, cold and temperature variability in five cities together resulted in 42,414 deaths during the study period, accounting for about 6.0% of all deaths. Fig. 3 compares the relative contribution of different temperature exposures to mortality burden. In general, most of the attributable deaths were from cold (61.4%), and then from temperature variability (28.0%) and heat (10.6%) (Fig. 3A), with substantial differences between cities. However, there was an exception for city Perth, where temperature variability caused more

Table 1
Descriptive statistics of data from the five largest cities in Australia, 2000–2009.

	Total deaths (no.)			Temperature (°C)		
	Warm season	Cold season	Whole study period	Warm season	Cold season	Whole study period
Adelaide	31,688	37,397	82,806	20.8 (11.3–36.8)	12.7 (6.3–23.0)	16.7 (6.3–36.8)
Brisbane	37,007	43,294	95,503	24.2 (18.0–33.0)	16.9 (6.1–26.4)	20.7 (6.1–33.0)
Melbourne	81,460	93,894	209,682	18.3 (7.4–35.4)	10.7 (4.6–21.0)	14.4 (4.6–35.4)
Perth	30,190	35,199	78,071	22.6 (13.5–33.2)	13.8 (6.6–24.2)	18.1 (6.6–33.2)
Sydney	89,966	113,716	242,689	21.9 (12.4–33.1)	14.7 (8.3–24.8)	18.4 (8.3–33.1)
Total	270,311	323,500	708,751	–	–	–

Temperatures are average city-specific daily mean temperature (range).
Warm season: January–March & November–December; Cold season: May–September.

deaths than heat and cold. Regarding the attributable fraction across cities, estimates for cold ranged from 3.2% in Perth to 11.2% in Brisbane, which is consistently larger than that for heat (range: 0% in Perth to 3.2% in Sydney) and temperature variability (range: 1.0% in Melbourne to 3.2% in Brisbane) (Fig. 3B).

To check the robustness of our models, we performed several sensitivity analyses for the associations of mortality with different temperature exposures. We changed the degree of freedom for time to control for long-term trend and seasonality; and adjusted for relative humidity and air pollution. All sensitivity analyses suggested our approaches were valid (data not shown).

4. Discussion

This study analysed the associations between three widely-reported temperature exposures and mortality in the five largest Australian cities, from 2000 to 2009. Exposure to either heat or cold or temperature variability was associated with increased mortality risk, with the highest risk posed by cold. The monotonic rising or declining trend in the mortality risk associated with any temperature exposures was not observed for the whole Australia, because such a pattern was evident only for some exposures in few cities and most cities witnessed apparent periodic or more complex fluctuations over the study period. It was estimated that those temperature exposures together were responsible for 6% of total deaths across all cities within study period. Most of this attributable mortality burden was caused by cold, followed by temperature variability and heat.

Numerous studies have examined the temperature-mortality association, most of which primarily reported on heat or cold effects. Findings from the largest-scale study to date demonstrated consistently greater cold effects than heat effects across multiple countries such as the USA, UK, China and Australia (Fig. 4), which is further supported here (Table 2) and elsewhere (Carson et al., 2006; Wang et al., 2017). However, opposite finding of larger heat effects than cold effects were also documented previously (Ma et al., 2014). This contrast seems possible because population acclimatization and adaptation, and climate characteristics are heterogeneous across different regions. Various study periods and a variety of modelling approaches may also contribute to the difference in heat and cold effects on mortality in prior findings.

Only one study, to the best of our knowledge, has compared temperature variability effects with heat/cold effects (Vicedo-Cabrera et al., 2016). This study, across three European cities and three USA cities, used intra-day or inter-day temperature change as temperature variability indicator and reported relatively small effects of temperature variability (Vicedo-Cabrera et al., 2016). As unstable weather is a continuous process and its effects can be delayed and persist several days (Guo et al., 2016), temperature variability effects were probably underestimated in some previous studies which individually investigated the intra-day or inter-day temperature change or failed to consider the lag effect (Vicedo-Cabrera et al., 2016; Lee et al., 2018). Also, the degree of temperature variability can be better captured by considering the intra-day and inter-day temperature change together (Guo et al., 2016). To address this challenge, some recent efforts have been made by considering temperature variability within two days (i.e., intra-day and inter-day temperature change) using temperature records at finer resolution such as hourly temperature (Cheng et al., 2017; Zhang et al., 2018). The lowest risk due to temperature variability among different temperature exposures was noted in the present study, which verified our earlier separate reports on the RR estimates for common temperature (heat and cold), and temperature variability (Fig. 4).

Progressive adaptation to the local harsh weather conditions already took place in many regions. Some countries, such as the USA, UK, Japan and Spain, generally witnessed continuously attenuated mortality risk from cold or heat during a period of time (Carson et al., 2006; Gasparrini et al., 2015b). Such reductions, however, was not observed in other countries including South Korea and Australia (Gasparrini et al., 2015b). The present study that used a relatively larger-scale dataset in Australia and controlled for the influence of temperature variability also suggested that there was no clear evidence of declining mortality risk from both cold and heat over time.

Also unclear is whether people have adapted to the unstable weather – temperature variability. Only two studies attempted to disentangle this question. One study by Zhang and his colleagues reported a

Table 2
The estimated relative risks of heat, cold and temperature variability in five largest cities of Australia, 2000–2009.

	RR (95% CI)			*P*-value
	Heat	Cold	Temperature variability	
Adelaide	1.008 (1.002–1.015)	1.018 (1.002–1.035)	1.005 (1.002–1.009)	Reference: heat
Brisbane	1.029 (1.013–1.045)	1.026 (1.010–1.044)	1.010 (1.005–1.015)	
Melbourne	1.016 (1.010–1.022)	1.019 (1.006–1.032)	1.003 (1.001–1.005)	*P*-cold = 0.017
Perth	1.001 (0.988–1.015)	1.014 (0.997–1.031)	1.004 (1.000–1.008)	
Sydney	1.009 (1.004–1.014)	1.021 (1.011–1.031)	1.006 (1.003–1.008)	*P*-temperature variability = 0.002
Australia	1.012 (1.007–1.017)	1.020 (1.014–1.026)	1.005 (1.003–1.007)	

RR: relative risk.
CI: confidence interval.
RR estimates for temperature variability were obtained from one previous study (Cheng et al., 2017).
RR estimates for Australia were obtained by pooling city-specific estimates with random-effects meta-analysis.
The between-exposure index (i.e., heat, cold and temperature variability) difference in effect estimates was tested using the meta-regression technique.

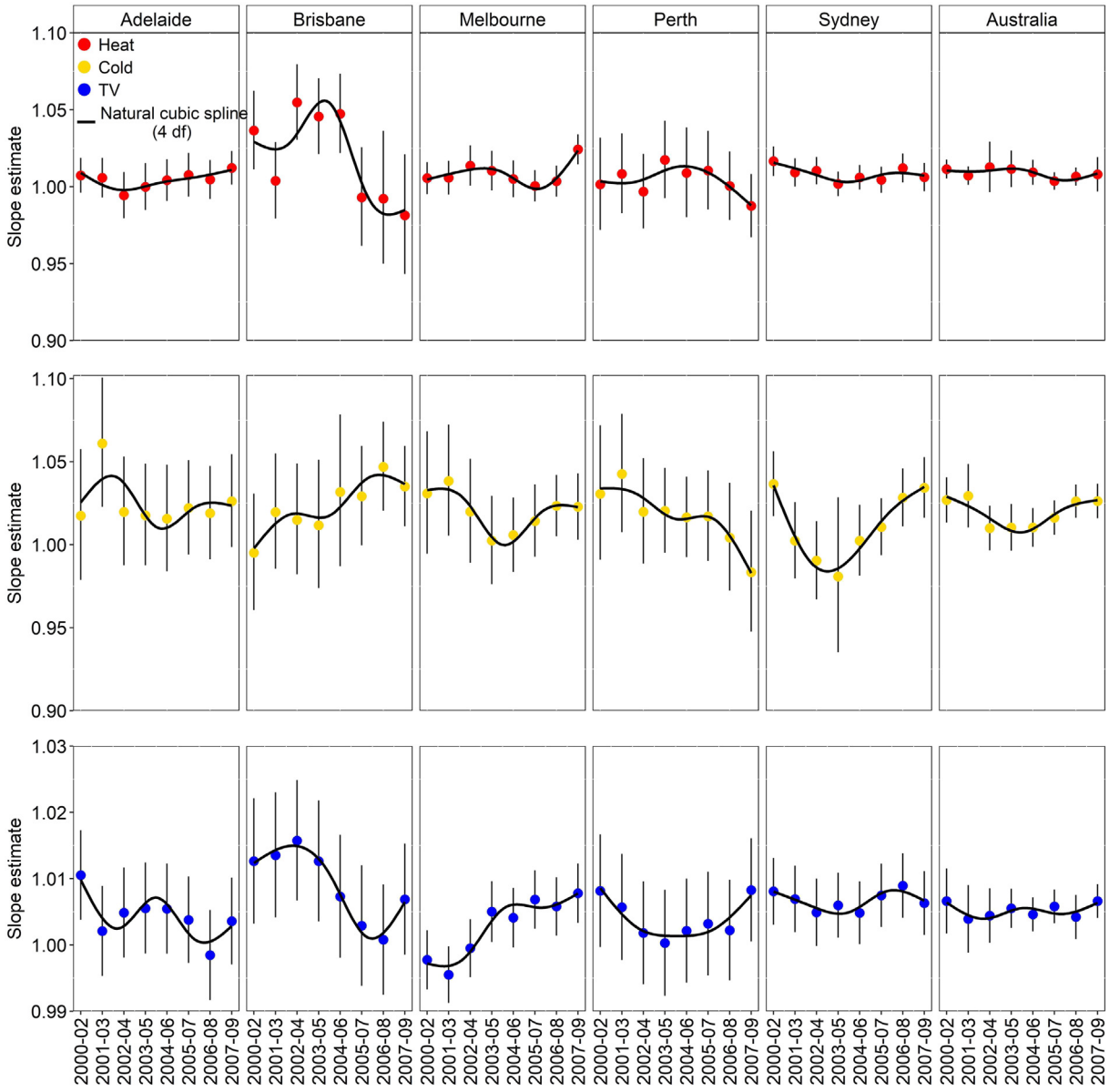

Fig. 2. The temporal variation in the association of mortality with heat, cold and temperature variability (TV) in Australia, 2000–2009. The slope (β) of temperature-mortality association was estimated and transformed with exp() function, which can be interpreted as the relative risk associated with per 1 °C change.

continuously reduced mortality burden over time in UK (Zhang et al., 2018), suggesting some extent of population adaptation. Another study by Lee et al. reported both decreasing and increasing mortality risk across countries (Lee et al., 2018). Adding to this important topic, we found relative stable mortality risk for the whole Australia. This indicates that population adaptation to unstable weather has not been well

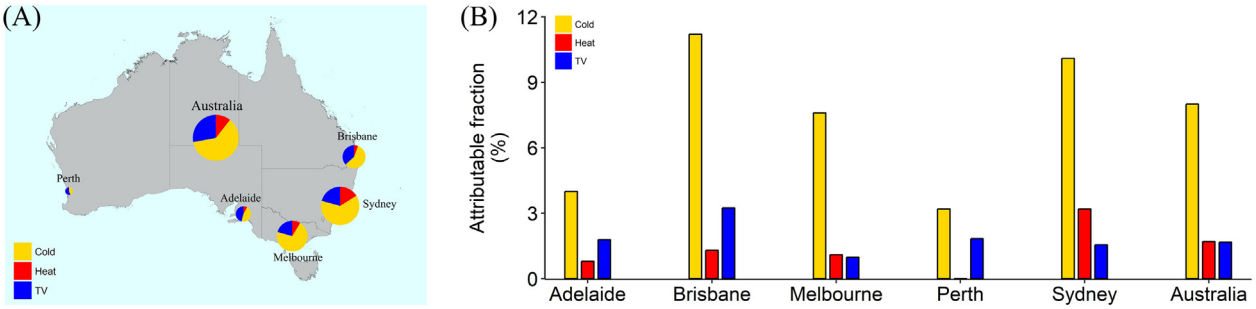

Fig. 3. Contributions of different temperature exposures to mortality: percentage of total attributable deaths from heat, cold and temperature variability (A) and city-specific attributable fraction (B). The size of pie charts was sorted by the city's population size; Calculation of attributable fraction for heat, cold and temperature variability (TV) was limited to warm season, cold season and the whole study period, respectively.

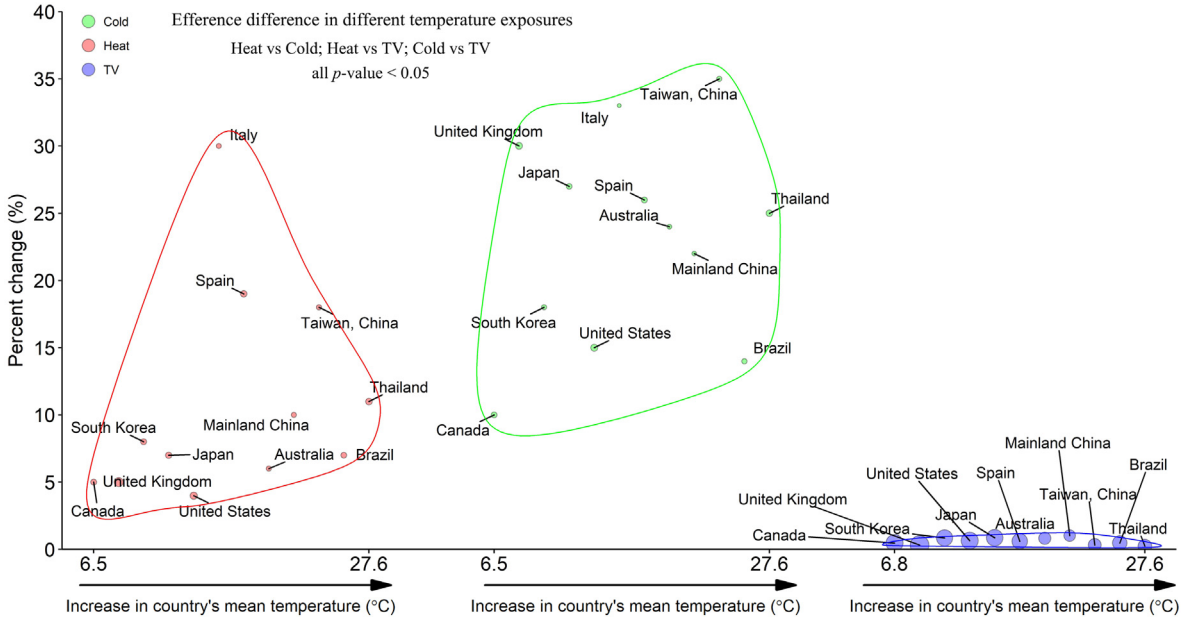

Fig. 4. The comparison of risk estimates (percentage change, %) for heat, cold and temperature variability (TV) across multiple countries. Relative risk (RR) estimates for each country were obtained from two previous studies (Guo et al., 2014; Guo et al., 2016), and then converted to percentage change (%) with formula: (RR-1) * 100%; The x-axis was scaled to each country's mean temperature (°C) for heat, cold and TV groups; The point size was determined by the inverse variance of estimated risk estimates. The effect difference between different temperature exposures was tested by meta-analysis regression.

established in most Australian cities, as the case of exposure to heat and cold. This situation that Australia confronted is different from many other regions which exhibit some adaptation to extreme temperature exposures (Lee et al., 2018; Gasparrini et al., 2015b). So, further research is urgently needed to understand why Australians have seemingly failed to get used to the local weather with the passage of time.

We estimated about 6.0% of deaths attributable to all temperature exposures in Australia, which is slightly lower than the attributable figure (about 7.0%) reported in a previous study (Gasparrini et al., 2015a). This difference may be because more regions and the influence of temperature variability were considered here. Nevertheless, our finding that most of mortality burden was caused by cold has previously been reported worldwide (Gasparrini et al., 2015a). One plausible explanation is that there are more cold days than hot days, causing relatively more frequent exposure to cold among populations. In the case of temperature variability versus cold, higher frequency of exposure to temperature variability can be expected. But the lowest mortality risk for temperature variability may dilute the severity of resulting disease burden. Thus, it is hard to predict the relative contribution of temperature variability among different temperature exposures and research in this specific area is not yet available (Guo et al., 2016; Guo et al., 2014). In this contribution, we quantified the mortality burden caused by different temperature exposures. Our findings revealed that the contribution of temperature variability ranked between cold and heat in most Australian cities, and even ranked first in one city (Perth) (Fig. 3A). This conclusion seems to be applicable to some Asian and European regions based on few studies that attributed the mortality burden to heat and cold, and temperature variability separately (Gasparrini et al., 2015a; Lee et al., 2017; Zhang et al., 2018).

This study had some limitations. First, we used the temperature records from the weather station as a proxy for individual exposure, which may cause measurement error. Second, although most of Australia's population are living in urban area and while the five Australian cities studied here cover a good proportion of that, it is difficult to generalize our findings to rural areas, where may have experienced different effects of non-optimum temperatures. Third, heat waves and cold spells have not been considered, which may to some extent influence the accuracy of effect estimates. However, we assumed that our results would not be materially changed because the contribution of heat waves and cold spells to mortality is little in the total temperature-related burden. Fourth, we only examined the all-cause mortality due to the issue of lack of availability of cause-specific data. Caution is needed when applying the results for some specific diseases because many outcomes such as death due to cancer may not be associated with temperature.

Our study also had some strengths. To our knowledge, this is the first study to comprehensively assess the effects of three different non-optimum temperature exposures on mortality from the perspective of both population vulnerability and disease burden, which would fill an important knowledge gap on the relative role of heat, cold and temperature variability in triggering mortality. The use of conventional effect estimates (RR) in conjunction with disease burden measures (attributable fraction and attribution number) will deepen our understanding of health impacts of temperature, including population vulnerability and resulting disease burden. The great importance of temperature variability in the total mortality burden has been reported for the first time. Our findings are important in prioritizing public health interventions to manage risk of different temperature exposures, regionally and nationally.

5. Conclusions

This study suggests significant associations between mortality and three well-known non-optimum temperatures in Australia, with cold posing the highest risk and temperature variability exerting the lowest risk in general. Consistent temporal decrease in the mortality risk was not observed for any temperature exposure in Australia. In addition to confirming previous finding that cold was generally responsible for the largest proportion of temperature-induced mortality burden, we found temperature variability made a greater contribution than heat in all cities studied, calling for future research to consider temperature variability when assessing and projecting temperature-related health impacts.

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Contributors

Jian Cheng, Zhiwei Xu and Wenbiao Hu designed the study, collected and prepared the data. Jian Cheng and Zhiwei Xu developed the statistical methods and conducted the data analysis; Jian Cheng took the lead in drafting the manuscript and interpretation of the results; Hilary Bambrick, Shilu Tong, Hong Su, Zhiwei Xu and Wenbiao Hu provided substantial scientific input in interpretation of the results and revision of the manuscript.

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Competing interests

None declared.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2018.10.186.

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